Towards physics-based segmentation of photograp color images

Luo, J. Gray, R.T. Hsien-Che Lee
Image Res. & Adv. Dev., Eastman Kodak Co., Rochester, NY, USA;

This paper appears in: **Image Processing, 1997. Proceedings., Internati Conference on**

Meeting Date: 10/26/1997 - 10/29/1997
Publication Date: 26-29 Oct. 1997
Location: Santa Barbara, CA USA
On page(s): 58 - 61 vol.3
Volume: 3
Reference Cited: 9
Number of Pages: 3 vol. (lii+951+892+748)
Inspec Accession Number: 5906488

Abstract:
In many digital image processing applications, image segmentation is require initial partitioning of local image regions based on certain statistical or contex homogeneity measures. One goal of image segmentation would be to segmer into regions that correspond to physically and semantically coherent objects i We propose an improved color segmentation algorithm by taking advantage c "k-mode" algorithm and an adaptive Bayesian k-means algorithm. The "k-mo algorithm uses a physics-based distance metric to generate regular partitionir color space. The adaptive k-means algorithm utilizes two additional mechanis spatial homogeneity constraints and spatial adaptivity, to achieve more robus coherent segmentation. The proposed algorithm integrates a physically more color space and the corresponding color difference metric into the the adaptiv K-means framework in an effort towards physics-based segmentation of phot color images

Index Terms:
Bayes methods adaptive signal processing image colour analysis image segmentat photography adaptive Bayesian k-means algorithm color difference metric color seg algorithm color space partitioning digital image processing applications image segm mode algorithm local image regions photographic color images physically coherent physics-based distance metric physics-based segmentation semantically coherent ob

adaptivity spatial homogeneity constraints

Documents that cite this document
There are no citing documents available in IEEE Xplore at this time.

Search Results [PDF FULL-TEXT 548 KB] PREV NEXT DOWNLOAD CITATION

Home | Log-out | Journals | Conference Proceedings | Standards | Search by Author | Basic Search | Advanced Search | Join IEEE | Web Account | New this week | OPAC Linking Information | Your Feedback | Technical Support | Email Alerting | No Robots Please | Release Notes | IEEE Online Publications | Help | FAQ| Terms | Back to Top

Towards Physics-based Segmentation of Photographic Color Images

Jiebo Luo *Robert T. Gray* *Hsien-Che Lee*
Imaging Research and Advanced Development
Eastman Kodak Company
Rochester, NY 14650, U.S.A.

Abstract

In many digital image processing applications, image segmentation is required to provide initial partitioning of local image regions based on certain statistical or contextual homogeneity measures. One goal of image segmentation would be to segment the image into regions that correspond to physically and semantically coherent objects in the scene. We propose an improved color segmentation algorithm by taking advantage of a simple "k-mode" algorithm and an adaptive Bayesian k-means algorithm. The "k-mode" algorithm uses a physics-based distance metric to generate regular partitioning of the color space. The adaptive k-means algorithm utilizes two additional mechanisms, i.e., spatial homogeneity constraints and spatial adaptivity, to achieve more robust and coherent segmentation. The proposed algorithm integrates a physically more meaningful color space and the corresponding color difference metric into the the adaptive Bayesian k-means framework in an effort towards physics-based segmentation of photographic color images.

1 Motivation

Image segmentation is a frequently encountered problem in many image processing tasks. While a "perfect" segmentation is very difficult, if not impossible, to accomplish without certain higher level interpretation, there is no doubt that the intelligence of many digital image processing algorithms can be greatly improved upon the extraction of semantically meaningful regions from the image scenes. For example, segmentation of distinctive objects in consumer photographic images can lead to the identification of main subject(s) and the background, and thus the optimal determination of exposure compensation. Segmentation of human flesh is of particular importance to many applications involving the detection of people, such as automatic personnel verification, human-computer interaction, etc.

Segmentation of color images has received significant attention from researchers [1, 2, 3, 4] because of the large amount of information contained in color images, complicated by such physical factors as surface orientation and illumination change, which make color image segmentation a very challenging task. In the past, many color segmentation methods have assumed that color is a constant property of an object and color variation is due to random camera noise. Consequently, these methods segment images not only along the material boundaries but also along other boundaries exhibiting color variations, such as highlight and shadow boundaries, or object edges with significant shading changes. Recently, physics-based segmentation has been attempted with initial successes [5, 6].

The proposed algorithm attempts to account for the physics of color variation in *low-level* statistical estimation rather than resorting to some higher level interpretation. This is achieved by the following: (1) selection of an appropriate color space, (2) design of a physics-based color difference measure, (3) coherent partitioning of the feature space, and (4) accommodation to local variation of the object properties and varying image capturing conditions. In short, the goal is to develop a general segmentation engine with good performance in terms of robustness to color variations and noise, and reasonable computational complexity. Important features of the proposed algorithm include:

- Utilization of a physics-based color space and color difference metric
- Utilization of spatial homogeneity constraints and spatial adaptivity
- Synergy of the above for improved segmentation
- Improved convergence

2 Color space and color difference metric for segmentation

The "k-mode" algorithm [5] is based on the partitioning of a carefully selected color space and a specific color difference measure. This color difference measure helps achieve physically coherent partitioning of the selected color space. The color space partitioning resembles a Voronoi partitioning with cells centered at the *modes* (or peaks) in the color histogram domain.

It has been recognized that a proper color space is of fundamental importance to color image segmentation [5, 7]. A color space transformation is equivalent to the feature extraction and feature selection processes typically involved in a pattern recognition task. In this study, a major concern is the relationship between the physical processes in the scene and the captured color image signals. It is desired that the

0-8186-8183-7/97 $10.00 © 1997 IEEE

natural causes of color variation within a coherent object should be discounted while the variations of color between distinct objects should be retained. After theoretical analysis and experimental tests, the (L, s, t) space was shown to be favored in most cases among a few eligible candidates [5]. Color spaces such as the CIE-LAB and CIE-LUV generally yield perceptually consistent results, but they are not chosen because *perceptual* difference is not necessarily a better metric for separating *physically* different materials. In particular, significant perceptual differences can occur even within a physically coherent object due to the shading generated by different lighting and surface orientation [7]. The (L, s, t) space is given in Equation (1). It consists of one luminance component L, and two chrominance components s and t. We use (R, G, B) to represent the film density or log exposure space. The two chrominance components are presumably invariant to intensity change of the lighting source. The s component approximately represents the illumination variation (daylight to tungsten light), and the t component is referred to as the green-magenta axis.

$$\begin{aligned} L &= \frac{1}{\sqrt{3}}(R+G+B) \\ s &= \frac{1}{\sqrt{2}}(R-B) \\ t &= \frac{1}{\sqrt{6}}(R-2G+B) \end{aligned} \tag{1}$$

Traditionally, some distance metric is used to associate the color difference or color similarity with mathematical quantities [8]. The Euclidean distance between two points in the selected color space is often used as a measure of the similarity of the respective colors for segmentation purposes. Note that here the *selected* color space is explicitly stated because the distance metric is closely related to the color space. However, Euclidean distance in the RGB space has not been found to be a consistent measure of color similarity [5, 7].

To partition the color space into volumes that preferably correspond to physically different objects, a few rules of thumb are considered appropriate. In general, the partition should be coarser in the luminance axis than in the chrominance axes. Furthermore, the partition should be coarser in color saturation than in hue. The former corresponds to discounting the effect of luminance variation and the latter reduces the effect of specular reflection. The formula for this physics-based distance [5] is given in Equation (2) where (W_l, W_s, W_h) are weighting factors for differences in the luminance, saturation and hue components, respectively. In general, we choose these weights such that $W_l << W_s < W_h$.

$$d = \sqrt{W_l * (\Delta lum)^2 + W_s * (\Delta sat)^2 + W_h * (\Delta hue)^2} \tag{2}$$

The color difference measure is defined with respect to the mode (peak) of each class, m, and a given point c, in (s,t) plane. It is decomposed into a pseudo "saturation" component, ΔP, and a pseudo "hue" component, ΔQ. Intuitively, "saturation" ΔP is parallel to the radial line from each center, and "hue" ΔQ is perpendicular to that line, as illustrated in Fig. 1.

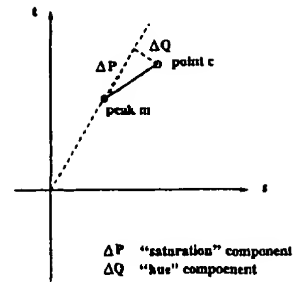

Figure 1: A physics-based distance measure.

3 The proposed algorithm

The proposed algorithm is based on color space partitioning with the incorporation of a Gibbs random field (GRF) model to account for spatial homogeneity constraints, and an adaptive mechanism to allow the *local* mean of each class to vary in spatial domain. The color of each region is modeled as a slowly varying *non-parametric* function plus noise. Spatial homogeneity constraints are imposed by a Gibbs random field model. Local color variations are accounted for in an iterative procedure involving the determination of the local class mean over a sliding window whose size decreases progressively. As a result, an image will be segmented into regions of *uniform, or more often, slowly varying* colors. This spatial adaptivity in essence attempts to account for color variations within objects, *in addition to* the adopted color difference metric. The original Bayesian adaptive segmentation algorithm for monochrome images was proposed by Pappas [9]. Chang *et al.* extended the Pappas algorithm to multichannel color images [7]. In this study, we modified Chang's algorithm to incorporate the preferred color space and color difference measure determined in the development of the "k-mode" algorithm [5], and also to improve the speed of execution. By incorporating the preferred color space and color difference measure into the adaptive k-means algorithm, not only does the "k-mode" algorithm serve as the initialization stage of the adaptive k-means algorithm, but the physics-based difference measure is also adopted throughout the entire iterative segmentation process. It is expected that more homogeneous, coherent, robust segmentation can be achieved.

The original adaptive Bayesian color segmentation [7] is formulated as a MAP estimation, as given in Equation (3). The estimated segmentation $\hat{x}$ is defined as the one that maximizes the posterior probability of the segmentation x given the observed data y, i.e., $p(x \mid y)$. Using Bayes rule, we have

$$\hat{x} = \arg\max p(x \mid y) = \arg\max p(y \mid x)p(x), \tag{3}$$

where $p(y \mid x)$ denotes the class conditional probability, and $p(x)$ denotes the *a priori* probability of the expected segmentation. A Gibbs random field is utilized to model and enforce spatial smoothness constraints as the image prior [7, 9]. The assumption that the conditional distribution of *each color component* of each class is modeled by an independent Gaussian PDF (probability density function) [7, 9] implies the use of Euclidean distance because the log-likelihood of a specific color belonging to a certain class will be proportional to its Euclidean distance to the mean color defined by the Gaussian PDF.

The introduction of the physics-based difference measure defined in Fig. 1 actually changes the original paradigm of MAP estimation. The new formulation can be considered as a *constrained* adaptive k-means clustering. There are three constraints in this sophisticated k-means procedure, namely, the spatial homogeneity constraints enforced by the GRF, the spatial adaptivity enforced by locally estimated means, and color similarity measure enforced by the physics-based difference measure. Such a constrained clustering algorithm is expected to reach a good synergism capable of generating a psychophysically coherent, robust, and noise resistant segmentation.

4 Experimental Results

With the incorporation of (L, s, t) color space and the physics-based color difference measure into the Bayesian adaptive k-means clustering, we obtain the class map in Fig. 2(g) starting from the initialization of Fig. 2(b). Notice that a more homogeneous segmentation is achieved. The class map of Fig. 2(g) and the associated *local* class means, are then used to generate the rendering in Fig. 2(h). It is the capability of allowing local means to vary in the spatial domain, and the binding of spatially adjacent pixels by the Gibbs random field and the physics-based color difference metric, that enables the cohesive segmentation of the flesh region, which has quite different surface orientations and is lit by quite different lighting.

From the experimental results with a Kodak image database, we have the observation that the marriage of the Bayesian adaptive k-means approach with the (L, s, t) color space and the physics-based color difference measure is well justified and does result in significant improvement in segmentation performance. It can be seen that the proposed method generates the most coherent segmentation results, as shown in Fig. 2(g) and 3(c). In particular, the white strip on the brown box emerges in the final segmentation of Fig. 3(c) even if it is not well defined in the initial segmentation of Fig. 3(b); all the flesh regions are classified into one class. The somewhat artificial breakup of the table can be fixed by a simple perceptual grouping procedure that merges neighboring regions with no strong boundaries in between. Furthermore, the computation efficiency is significantly improved in the current implementation. For example, it takes a total of 192 seconds on a Sun Sparc 20 workstation to obtain the segmentation in Fig. 2(f) using Chang's algorithm. On the other hand, it takes only 7 seconds for the proposed algorithm to get Fig. 2(g). The faster convergence is partly due to the elimination of unnecessary iterations after the termination criterion is met for the current cycle. In addition, we believe that the selections of the color space and color difference measure appropriate to segmentation contribute to the improved performance in terms of physically more coherent segmentation and faster convergence (fewer cycles and fewer iterations per cycle), although a more rigorous explanation is desired. Intuitively, color features corresponding to object color appearance are better clustered in the selected color space, and the clustering process is more effective using the selected color difference measure.

5 Conclusion and Future Work

In the future, a multiresolution implementation of the multichannel Bayesian adaptive k-means algorithm along the lines suggested by Pappas [9] is planned in order to further improve its speed and performance. It is expected that progressive coarse-to-fine segmentation will deter undesired class splitting and unnecessary class change during the iterations.

References

[1] R. M. Haralick and L. G. Shapiro, "Image segmentation techniques," *CVGIP: Graphical Models and Image Processing*, vol. 29, pp. 100–132, 1985.

[2] G. Healy, "Using color for geometry-insensitive segmentation," *J. Opt. Soc. Am.*, vol. 6, no. 6, pp. 920-937, 1989.

[3] G. J. Klinker, S. A. Shafer, and T. Kanade, "A physical approach to color image understanding," *Int. J. Comput. Vision*, vol. 4, no. 1, pp. 7–38, 1990.

[4] Y. W. Lim and S. U. Lee, "On the color image segmentation algorithm based on the thresholding and the fuzzy c-means techniques," *Pattern Recognit.*, vol. 21, no. 9, pp. 935–952, 1990.

[5] H.-C. Lee, "Color image quantization based on physics and psychophysics," *J. Soc. Photogr. Sci. Technol. Jpn.*, vol. 59, no. 1, pp. 212–225, 1996.

[6] B. A. Maxwell and S. A. Shafer, "Physics-based segmentation: Moving beyond color," in *Conf. Comput. Vision Pattern. Recognit.*, 1996.

[7] M. M. Chang, M. I. Sezan, and A. M. Tekalp, "Adaptive Bayesian estimation of color images," *J. Electron. Imaging*, vol. 3, pp. 404–414, October 1994.

[8] R. W. G. Hunt, *Measuring Colour.* Chichester, England: Ellis Horwood, 1987.

[9] T. Pappas, "An adaptive clustering algorithm for image segmentation," *IEEE Trans. Signal Process.*, vol. 40, pp. 901–914, 1992.

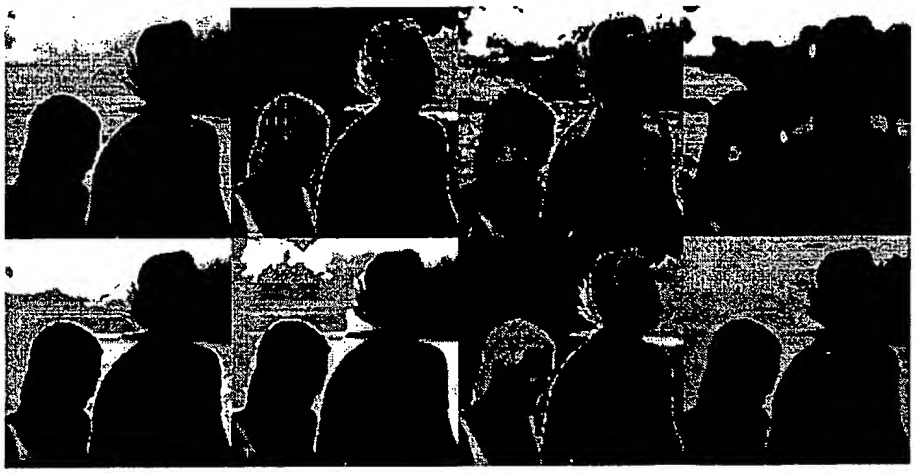

Figure 2: Comparison of the segmentation results in raster scan order: (a) original image, (b) class map by "k-mode" segmentation, (c) class map by k-means clustering in RGB space, (d) class map by Bayesian adaptive k-means clustering in RGB space, (e) class map by k-means in CIELAB-like space, (f) class map by Bayesian adaptive k-means clustering in CIELAB-like space, (g) class map by the proposed algorithm, (h) rendered segmentation by the proposed algorithm.

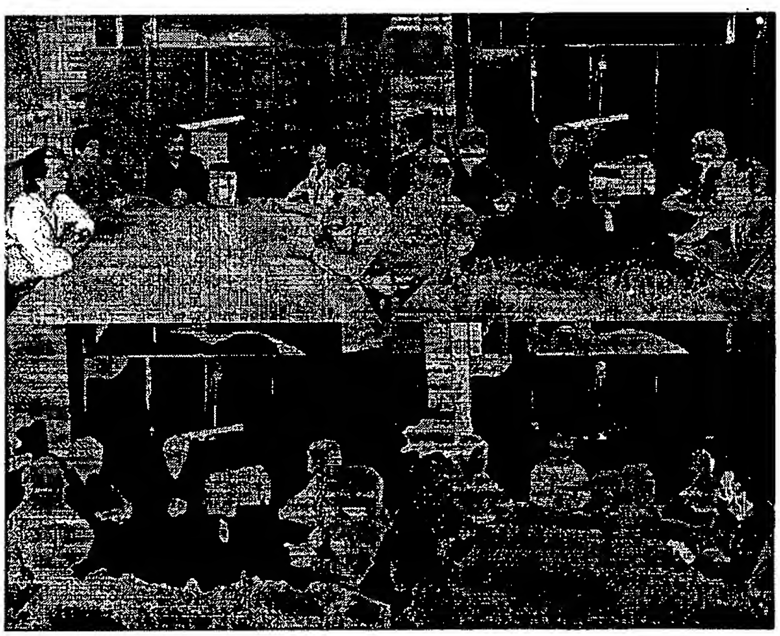

Figure 3: Segmentation results in raster scan order: (a) original image, (b) class map by "k-mode" segmentation, (c) class map by the proposed algorithm, (d) class map by the proposed algorithm after connected component analysis.

Your search matched **14** of **1015452** documents.
A maximum of **500** results are displayed, **15** to a page, sorted by **Relevance** **Descending** order.

Refine This Search:
You may refine your search by editing the current search expression or enter new one in the text box.

belief and pixel [Search]

☐ Check to search within this result set

Results Key:
JNL = Journal or Magazine **CNF** = Conference **STD** = Standard

---

1 **Combining belief networks and neural networks for scene segment**
Xiaojuan Feng; Williams, C.K.I.; Felderhof, S.N.;
Pattern Analysis and Machine Intelligence, IEEE Transactions on , Volume: 24 , Issue: 4 , April 2002
Pages:467 - 483

[Abstract] [PDF Full-Text (665 KB)] **IEEE JNL**

---

2 **A physics-motivated approach to detecting sky in photographs**
Jiebo Luo; Etz, S.;
Pattern Recognition, 2002. Proceedings. 16th International Conference on , Volume: 1 , 11-15 Aug. 2002
Pages:155 - 158 vol.1

[Abstract] [PDF Full-Text (368 KB)] **IEEE CNF**

---

3 **Facial expression analysis by integrating information of feature-poi positions and gray levels of facial images**
Shinza, Y.; Saito, Y.; Kenmochi, Y.; Kotani, K.;
Image Processing, 2000. Proceedings. 2000 International Conference on , Vo 1 , 10-13 Sept. 2000
Pages:466 - 469 vol.1

[Abstract] [PDF Full-Text (280 KB)] **IEEE CNF**

---

4 **Probabilistic robot localization and situated feature focusing**
Motomura, Y.; Vlassis, N.; Krose, B.;
Systems, Man, and Cybernetics, 1999. IEEE SMC '99 Conference Proceedings IEEE International Conference on , Volume: 4 , 12-15 Oct. 1999
Pages:726 - 730 vol.4

[Abstract] [PDF Full-Text (372 KB)] **IEEE CNF**

---

5 **Detecting the wall-motion of the fetal heart within ultrasound imag**
Gibson, S.H.; Villanueva, H.E.; Falconer, J.;
Engineering in Medicine and Biology Society, 1996. Bridging Disciplines for Biomedicine. Proceedings of the 18th Annual International Conference of the IEEE , Volume: 2 , 31 Oct.-3 Nov. 1996
Pages:883 - 884 vol.2

[Abstract] [PDF Full-Text (212 KB)] **IEEE CNF**

---

6 **Empirical Bayesian EM-based motion segmentation**
Vasconcelos, N.; Lippman, A.;
Computer Vision and Pattern Recognition, 1997. Proceedings., 1997 IEEE Computer Society Conference on , 17-19 June 1997
Pages:527 - 532

[Abstract] [PDF Full-Text (640 KB)] **IEEE CNF**

---

7 **Biometric identification system by lip shape**
Gomez, E.; Travieso, C.M.; Briceno, J.C.; Ferrer, M.A.;
Security Technology, 2002. Proceedings. 36th Annual 2002 International Carı Conference on , 20-24 Oct. 2002
Pages:39 - 42

[Abstract] [PDF Full-Text (358 KB)] **IEEE CNF**

---

8 **The suitability of the Java language for computer-graphics and visualisation research**
Devai, F.; Rahman, M.;
Information Visualisation, 2002. Proceedings. Sixth International Conference on , 10-12 July 2002
Pages:273 - 278

[Abstract] [PDF Full-Text (262 KB)] **IEEE CNF**

---

9 **A multiresolution based method for recognizing weeds in corn field:**
Chapron, M.; Boissard, P.; Assemat, L.;
Pattern Recognition, 2000. Proceedings. 15th International Conference on , Volume: 2 , 3-7 Sept 2000
Pages:303 - 306 vol.2

[Abstract] [PDF Full-Text (448 KB)] **IEEE CNF**

---

10 **Multisource data and knowledge fusion for intelligent SAR sea ice classification**
Soh, L.-K.; Tsatsoulis, C.;
Geoscience and Remote Sensing Symposium, 1999. IGARSS '99 Proceedings. 1999 International , Volume: 1 , 28 June-2 July 1999
Pages:68 - 70 vol.1

[Abstract] [PDF Full-Text (276 KB)] **IEEE CNF**

---

11 **What can SPECT learn from autoradiography?**
Gindi, G.; Rangarajan, A.;
Nuclear Science Symposium and Medical Imaging Conference, 1994., 1994 IE
Conference Record , Volume: 4 , 30 Oct.-5 Nov. 1994
Pages:1715 - 1719 vol.4

[Abstract] [PDF Full-Text (384 KB)] **IEEE CNF**

---

12 **Spatially coherent clustering applied to cardiac angiograms**
Kottke, D.P.;
Bioengineering Conference, 1992., Proceedings of the 1992 Eighteenth IEEE /
Northeast , 12-13 March 1992
Pages:11 - 12

[Abstract] [PDF Full-Text (196 KB)] **IEEE CNF**

---

13 **Functional templates and their application to 3-D object recognitio**
Delanoy, R.L.; Verly, J.G.; Dudgeon, D.E.;
Acoustics, Speech, and Signal Processing, 1992. ICASSP-92., 1992 IEEE
International Conference on , Volume: 3 , 23-26 March 1992
Pages:141 - 144 vol.3

[Abstract] [PDF Full-Text (396 KB)] **IEEE CNF**

---

14 **Representation and transformation of uncertainty in an evidence tl framework**
Betz, J.W.; Prince, J.L.; Bello, M.G.;
Computer Vision and Pattern Recognition, 1989. Proceedings CVPR '89., IEEE
Computer Society Conference on , 4-8 June 1989
Pages:646 - 652

[Abstract] [PDF Full-Text (576 KB)] **IEEE CNF**
